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# Benchmarking, Monitoring, Observability, and Experimenting for Big Data and Machine Learning Systems

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# Learning objectives

- Able to analyze  the role of measurement, monitoring and observability in real-world cases for R3E
- Understand and develop methods with key steps and important tools for  benchmarking, monitoring, observability and experimenting
- Able to apply these methods for big data/ML systems

# The role of measurement, monitoring and observability

# Development vs Runtime activities

## Design, test and benchmark R3E

- R3E for individual components
- model/capture complex dependencies
- design logs, metrics and traces for capturing states and complex dependencies

## Monitoring/observability and runtime adaptation

- runtime monitoring and observability
- states, performance and failure analytics
- runtime controls (constraints, rules, actions)

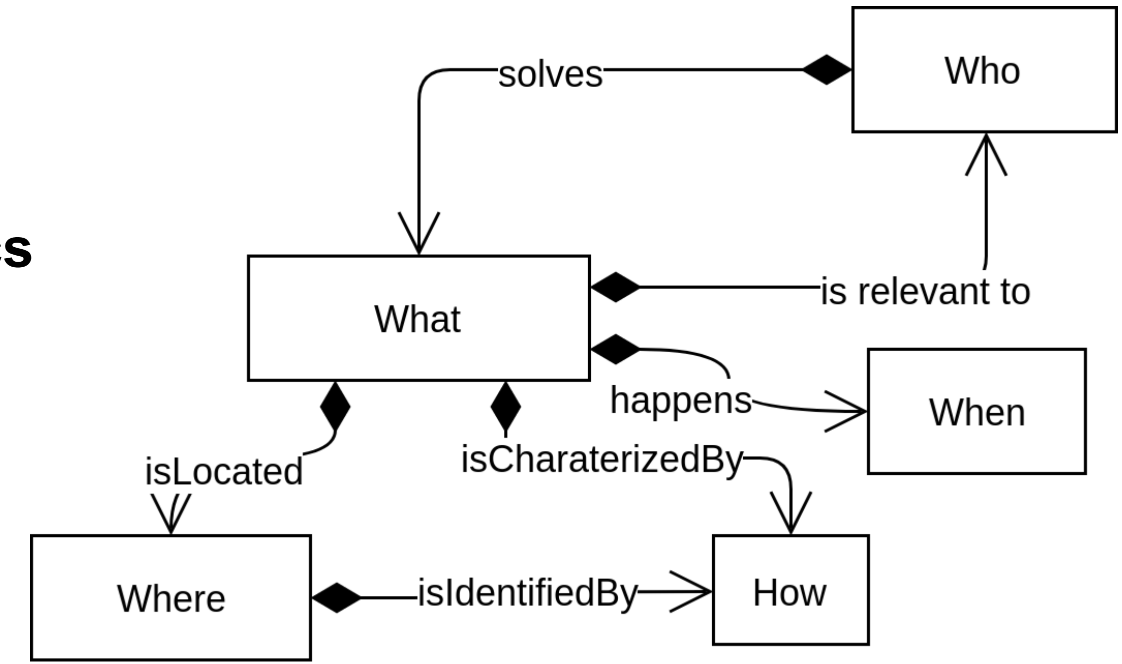
# Measurement, monitoring, and observability for R3E

- **Instrumentation and sampling**
  - instrumentation: insert probes into systems to measure system behaviors directly or produce logs
  - sampling: use components to sample system behaviors
- **Monitoring**
  - perform sampling or instrumentation to collect and share metrics, logs, traces; visualize what has been happened
- **Observability**
  - evaluate and interpret measurements for specific contexts
  - understand  and explain the systems states, dependencies, etc.

# Methods

# What/Which, Where, When, Who and How

**Understand W4H aspects for analytics of big data/ML systems**



# Key steps – What/Which

- **Understand and identify indicators/metrics characterizing your systems**
- **Common metrics vs specific (big data/ML) ones**
  - different relevance/importance based on specific contexts
- **Most critical problems are due to complex dependencies that are not common**
  - root cause analysis will be tricky
- **For which purposes?**
  - SRE, benchmarking, Test-Driven Development (TDD)

# Key steps – Where and When

- **Where: as a “ space” dimension**
  - tightly coupled or isolated/loosely coupled
  - different places
    - software/system layers, components and systems boundaries
    - dependencies among components
    - development/configuration pipelines
- **When: as a „time“ dimension**
  - design, test/training, or runtime (DevOps)
  - further divided into sub states

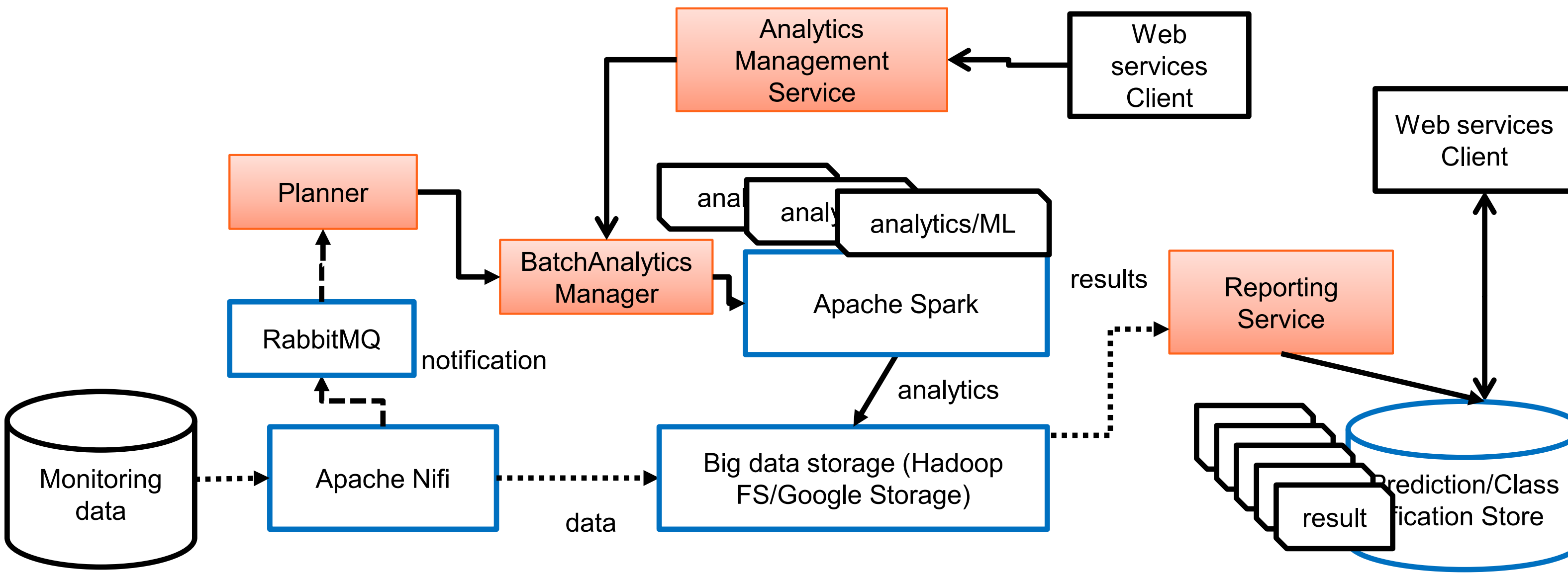
# Key steps - How

- **Characterize dependencies among components**
  - understand the system as a whole
  - include also development processes, data, software artefacts and execution environments
- **Select tools for capturing metrics**
- **Understand what kind of changes/designs we must do**
- **Do monitoring and analysis**
- **Integrate many types of data for monitoring and observability**

# Apply W4H for benchmarking, monitoring, validation and experimenting

- **Determines clearly system boundaries**
  - the system under study, the system used to judge, and the environment
  - "domain-driven/oriented" and bounded context principles
- **Understands dependencies**
  - among components in distributed big data/ML systems in distributed computing platforms
  - single layer as well as cross-layered dependencies
- **Determines types of metrics and failures and break down problems along the dependency path (how)**

# Boundaries and dependencies?



# Boundaries and dependencies

- **E.g., for testing/debugging**
  - Data?
  - Model?
  - Underlying service platform?
  - Or all of them?

**Example of a ML service for object recognition (used in our hands-on)**

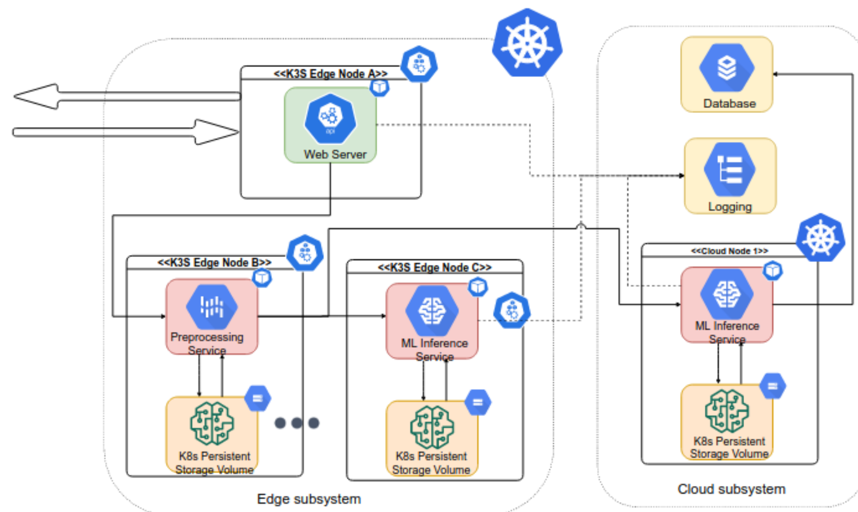
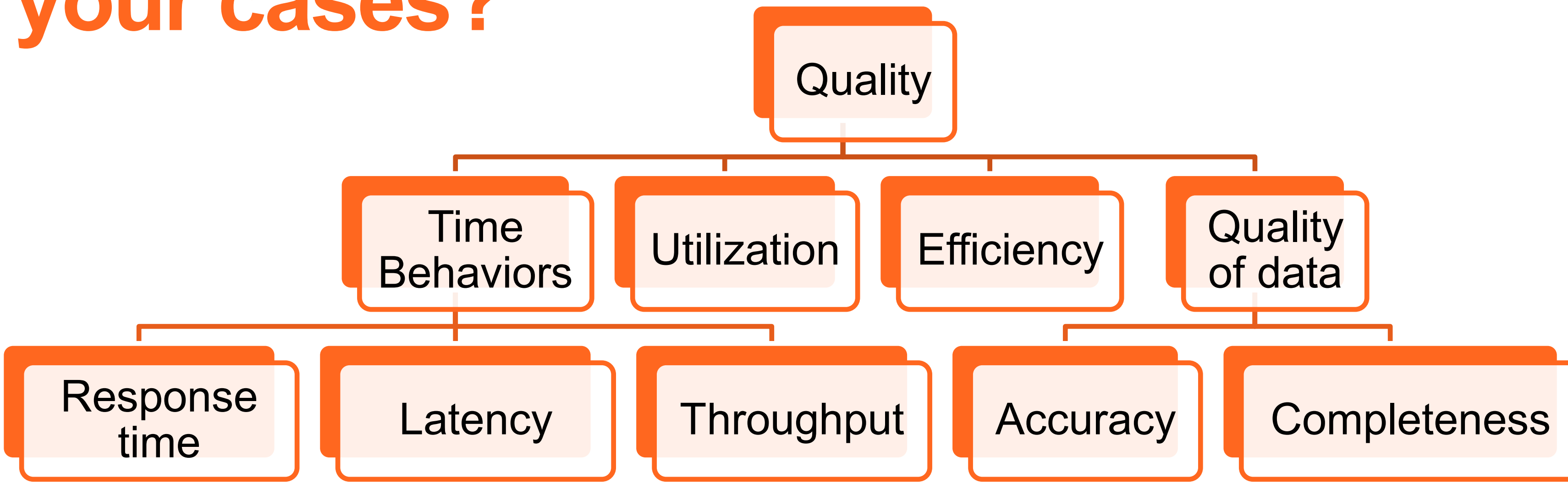



**Figure source :Rohit Raj, "Establishing trust for secure elasticity in edge-cloud microservices", https://aaltodoc.aalto.fi/handle/123456789/110507**

# What are the most critical metrics for your cases?



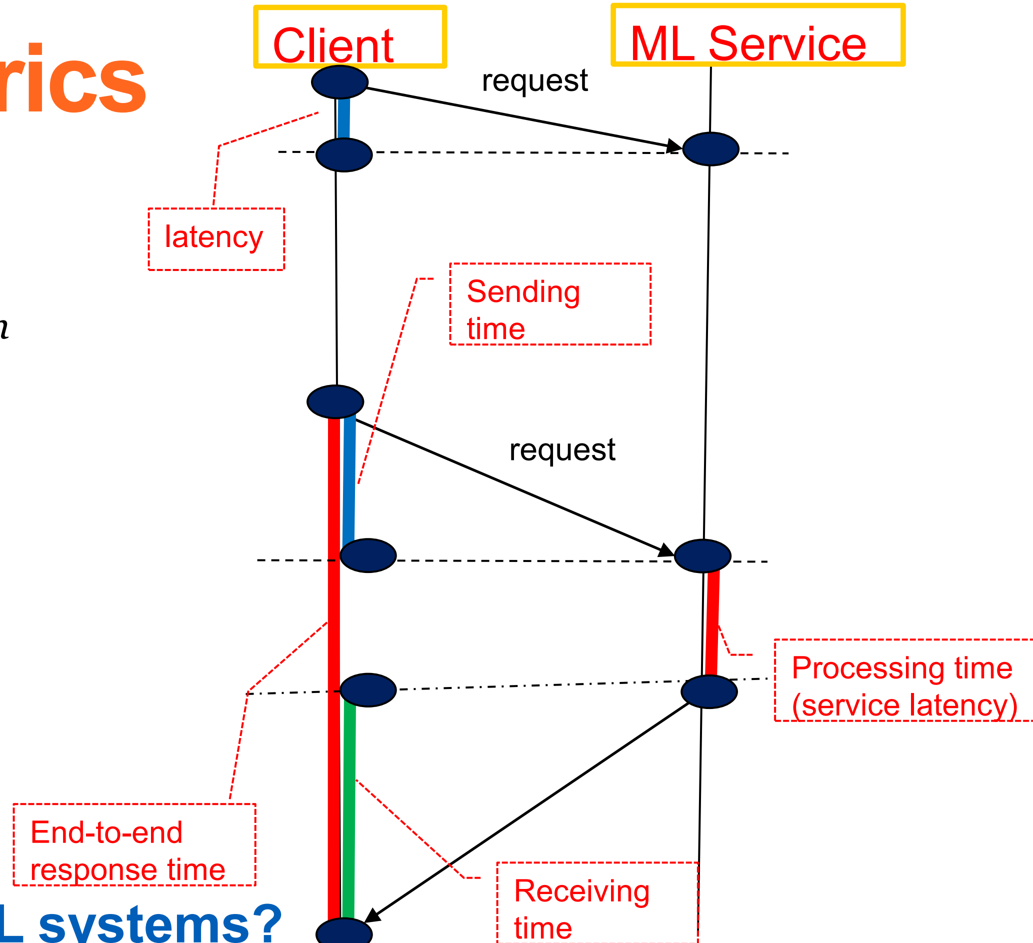

Industry view: https://guidingmetrics.com/content/cloud-services-industrys-10-most-critical-metrics/
NIST: https://www.nist.gov/sites/default/files/documents/itl/cloud/RATAX-CloudServiceMetricsDescription-DRAFT-20141111.pdf

**Contradiction/Tradeoffs between Efficiency versus Resiliency**
**Metrics for an ML model =! Metrics for ML system**

# Common performance metrics

- **Timing behaviors**
  - Communication
    - *Latency/Transfer time*
    - *Data transfer rate, bandwidth*
  - Processing
    - *Response time (service latency/time)*
    - *Throughput*
- **Utilization**
  - Network utilization
  - CPU utilization
  - Service utilization
- **Efficiency/Scalability**
  - Concurrent executions

Examples




**are they enough for big data/ML systems?**

# Types of Failure

**Common**

- Type of failures
  - Crash failures
  - Omission failures
  - Timing failures
  - Response failures
  - Arbitrary/ Byzantine failures

**But unforeseen failures cannot be determined in advance → design for handling failure**

**Check: https://arxiv.org/pdf/1910.11015.pdf for a “Taxonomy of Real Faults in Deep Learning Systems”**

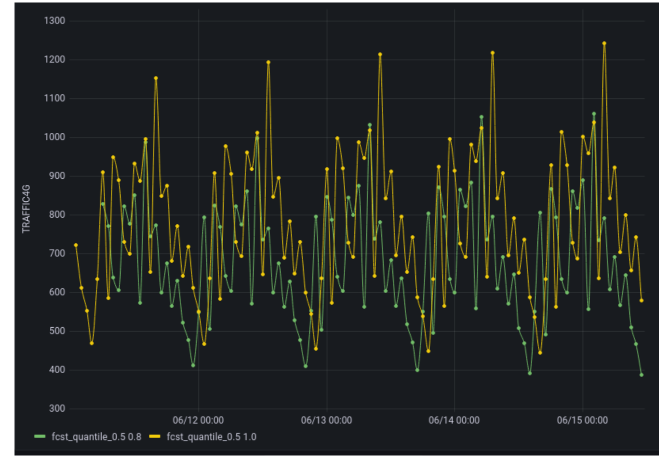
# Metrics for Data

- Completeness
- Timeliness
- Currency
- Validity
- Format
- Accuracy
- Data  Drift

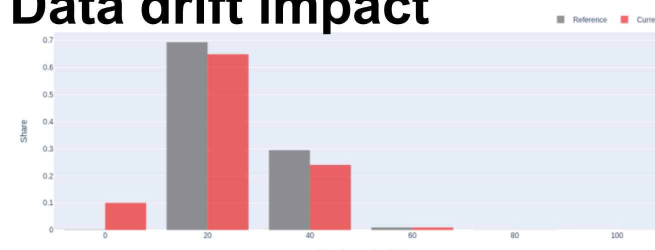
Understand the impact

Often evaluation methods are different for different types of data

**Forecasting**




**Data drift impact**




**(Examples with real mobile data)**

# Metrics for ML models

- Confusion matrix
- Accuracy
- Loss
- True positive rate
- False positive rate
- F1 Score/F-measure
- Etc.

(see https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234)

**How would we define "reliable function" of the model? E.g., when should we "retrain" the model?**

How can we relate them to ML service/system?

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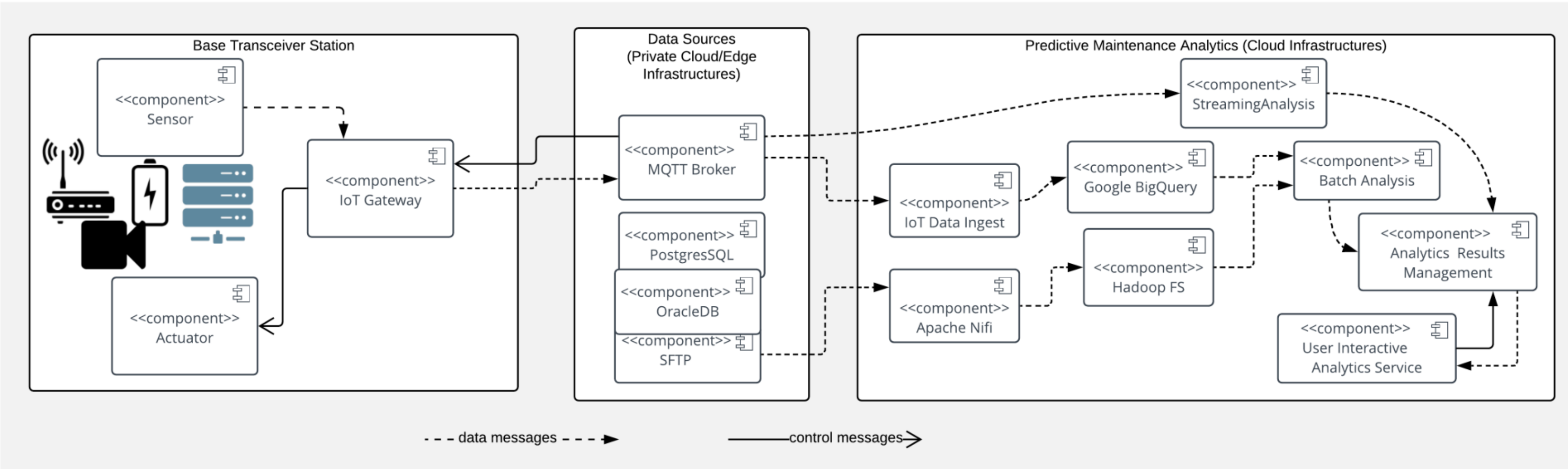
# Benchmarking, Observability and R3E Handling

# Benchmarking

- **Benchmark: for comparing big data/ML systems w.r.t. selected (standard/common) workloads**
- **Where to be benchmarked**
  - benchmark individual subsystems: message brokers and data ingestion, databases and ingestion/query, data processing, ML models, serving platform
- **What to be benchmarked**
  - data ingestion throughput, processing throughput and time, component CPU and memory
  - training and inferencing time and accuracy

# Benchmarking

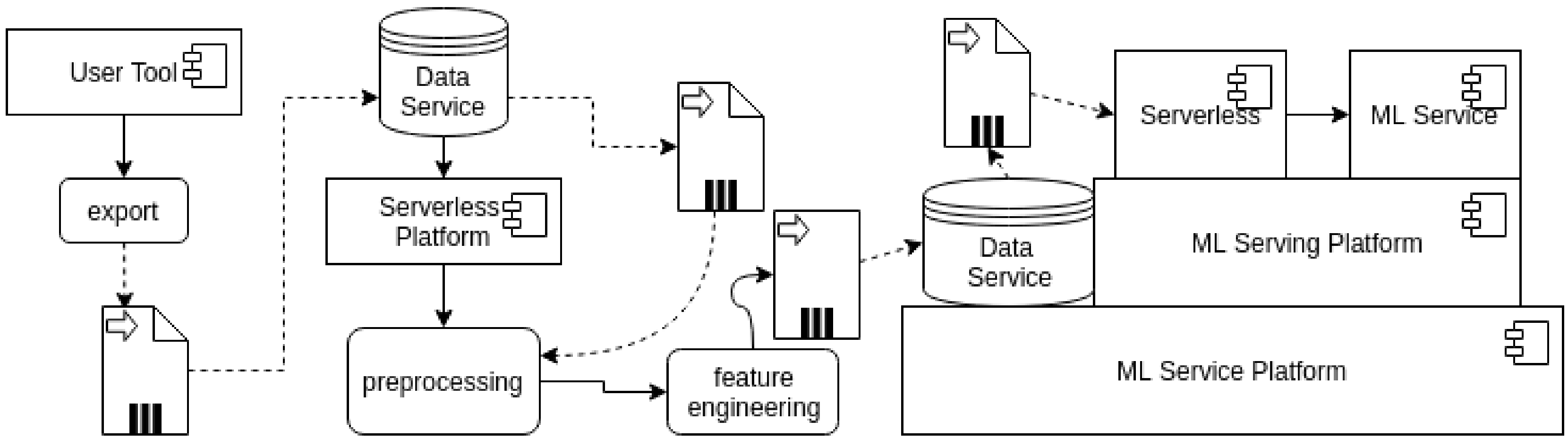
## What should we do for a big data system?




Check:
https://www.sciencedirect.com/science/article/pii/S0140366419312344
https://www.benchcouncil.org/BigDataBench/

# Benchmarking

## If you have an end-to-end ML system, does it make sense to benchmark the whole system?



# Benchmarking - ML

## Examples:

| Benchmark results (minutes) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Image classification** | **Image segmentation (medical)** | **Object detection, light-weight** | **Object detection, heavy-weight** | **Speech recognition** | **NLP** | **Recom-mendation** | **Reinforce-ment Learning** |
| ImageNet | KiTS19 | COCO | COCO | LibriSpeech | Wikipedia | 1TB Clickthrough | Go |
| ResNet | 3D U-Net | SSD | Mask R-CNN | RNN-T | BERT [1] | DLRM | Minigo |

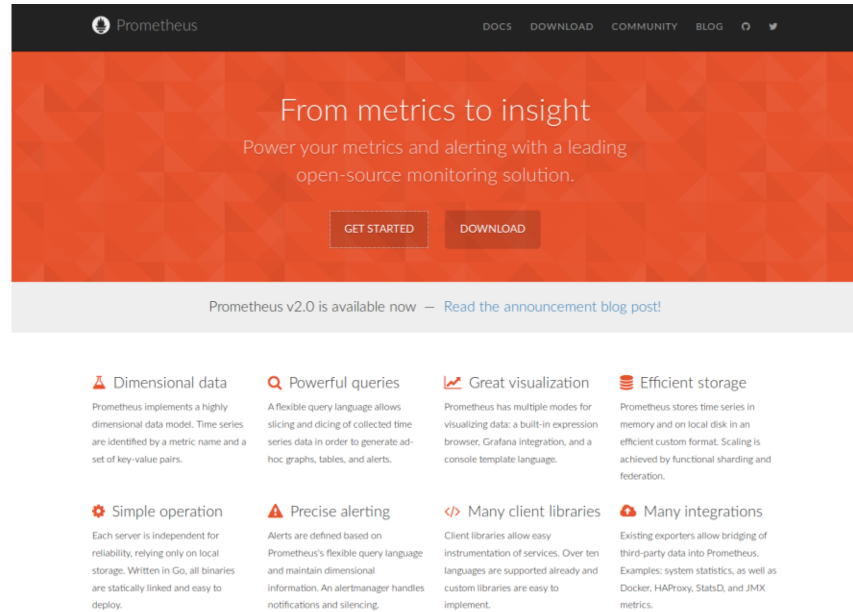
Source: https://mlcommons.org/en/training-normal-10/

**Also check: https://www.benchcouncil.org/AIBench/index.html**

# Service/Infrastructure monitoring tools

**There are many powerful tools!**

**But only low-level, well-identified monitoring data (infrastructures): pre-defined metrics exposed through interfaces with push/pull mechanism**




From: https://prometheus.io/

# Instrumentation for observability

**Code instrumentation: for many metrics and logs that cannot be obtained from the outside of the component**

**→**

**the developer can instrument the code to capture metrics/generate logs/traces**


From: https://www.fluentd.org/

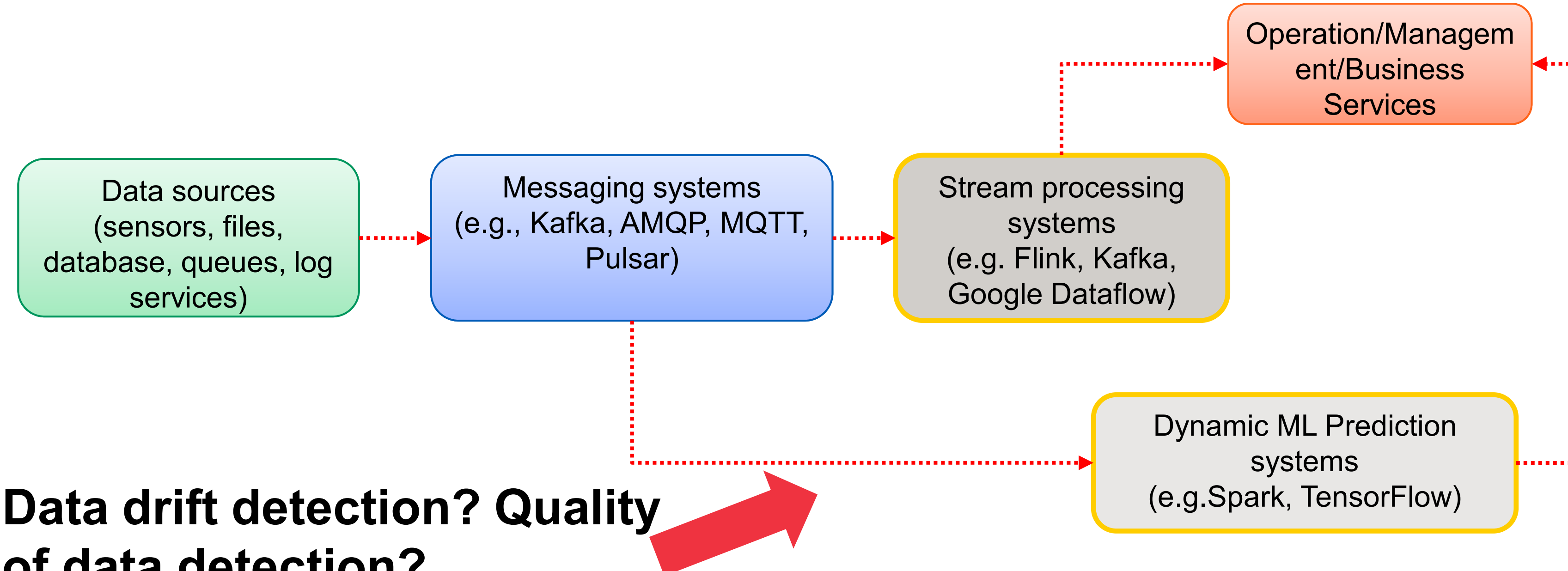
**Filebeat**

**Lightweight shipper for logs**

**https://www.elastic.co/beats/filebeat**

**https://opentelemetry.io/**

# Can we capture data metrics on-the-fly? For which use cases?

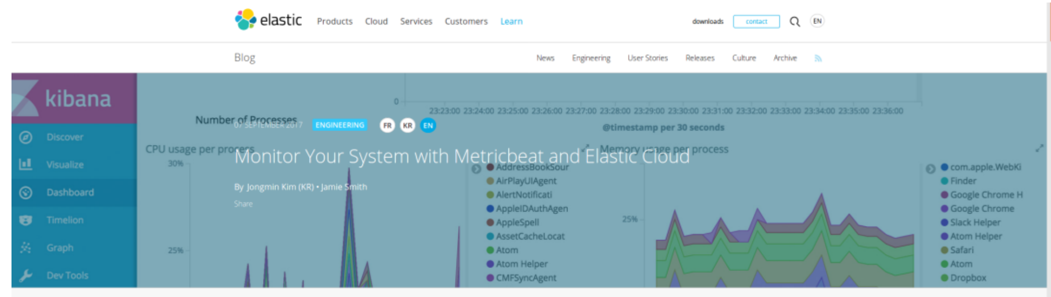



**Data drift detection? Quality of data detection?**
**Or performance prediction?**

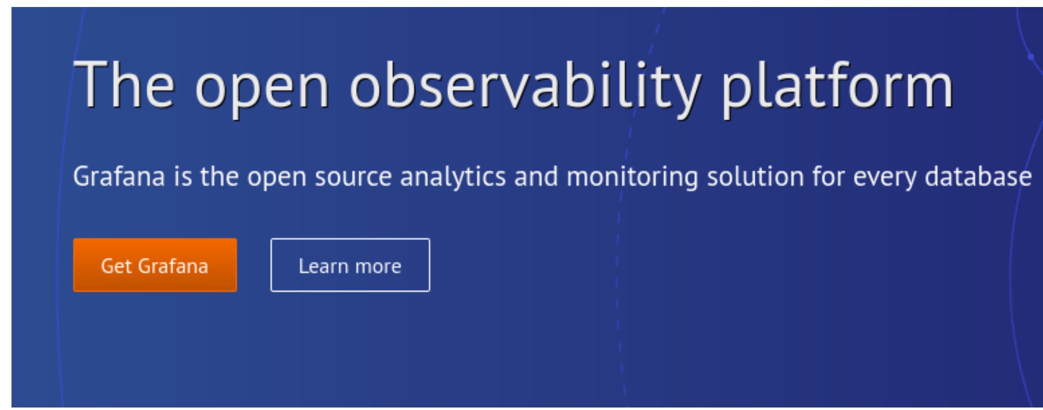
# Visualization

## Metrics and Visualization

- **Easy to visualize many types of metrics**
  - Human-in-the-loop
- **But only you can specify, define and map them to your applications**
- **Not for process automation!**
  - further integration and intelligence analytics (ML?)




https://www.elastic.co/products/kibana




https://grafana.com/

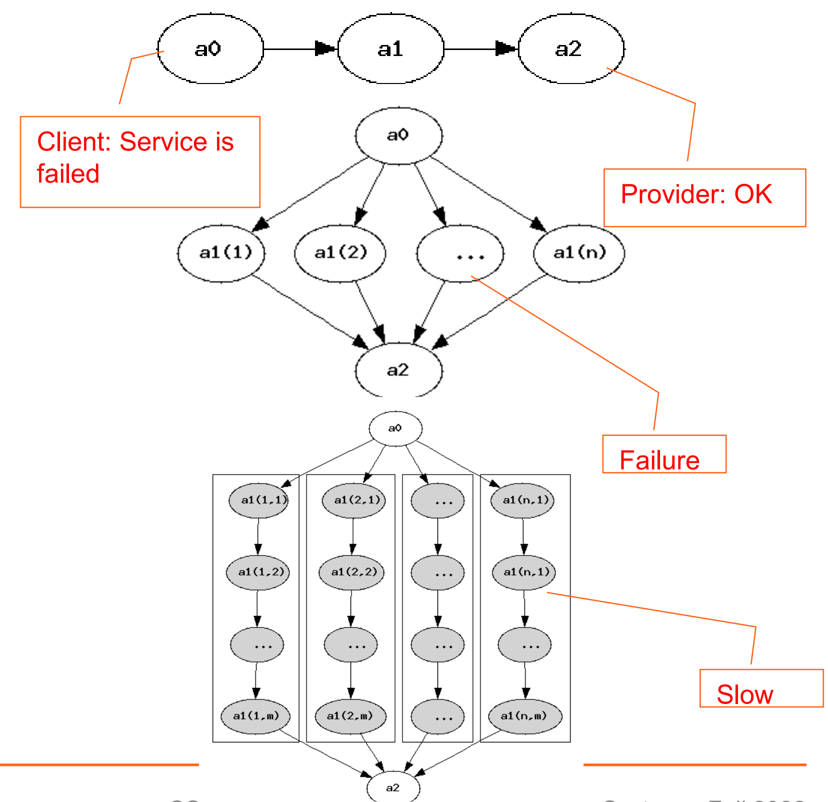
# Observability

- **To monitor and understand the system as whole, end-to-end**
  - every component must be monitored
  - dependencies/interactions must be captured
  - diverse metrics, logs, tracing, etc. are needed to be integrated
- **Understand the states and behaviors of the whole systems**
- **Complex problems in big data/ML systems as these systems**
  - large-scale number of microservices in large-scale virtualized infrastructures
  - multi-dimensional states (code, models and data)

# Do we understand the structure of big data/ML application

- **Composable method**
  - divide a complex structure into basic common structures
  - each basic structure has different ways to analyze specific failures/metrics
- **Interpretation based on context/view**
  - client view or service provider view?
  - conformity versus specific requirement assessment

Dependency Structure



# Support an end-to-end view or not

- **End-to-end reflects the entire system**
  - e.g., data reliability: from sensors to the final analytics/inference results
  - what if the developer/provider cannot support end-to-end?
- **The user expects end-to-end R3E**
  - e.g., specified in the expected accuracy
- **Providers/operators want to guarantee end-to-end quality**
  - need to monitor different parts, each has subsystems/components
  - coordination-aware assurance, e.g., using elasticity

# Techniques for addressing problems in different system/software layers

- **Immutable infrastructures: containers and orchestration**
  - shared nothing for isolation, redundancy elasticity, auto-recovery
- **Services:**
  - redundancy, data/function sharding, microservices for isolation, elasticity/autoscaling-based, stateless
- **Tasks:**
  - fault-tolerance, retries, delegation
- **Interactions/requests**
  - service-based, well-defined protocols for isolation, asynchrononous modes for isolation, elasticity,  handling cascading failures

# Example: resilience implementation strategies for request handling

- **Component/service replication**
  - multiple instances, both data and function sharding
- **Component/service isolation**
  - asynchronous communications among services, microservices (virtualization/containers), share nothing infrastructural design, failure isolation, well-defined protocols
- **Component/service function delegation**
  - hand over the tasks to other components through task distribution/orchestration via workflows, queues and serverless

# Example: resilience implementation strategies for request handling

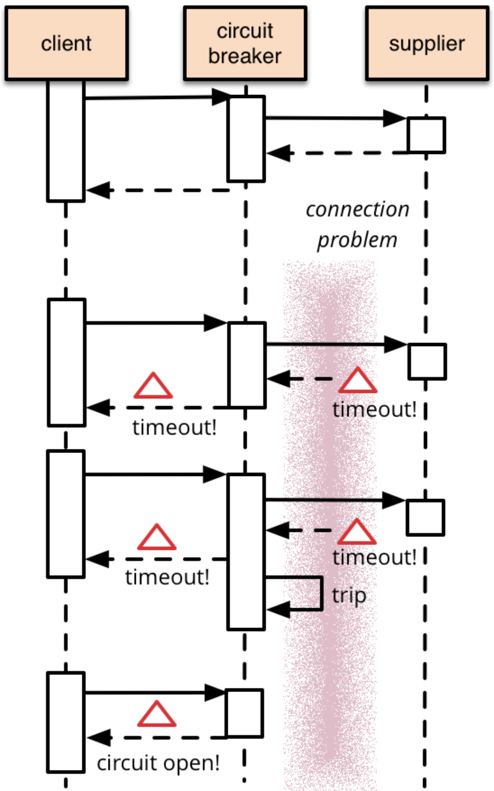
- **Throttling Pattern**
- **Circuit breaker pattern**
- **Queue-based Load Levelling Pattern**
  - https://docs.microsoft.com/en-us/azure/architecture/patterns/queue-based-load-leveling
- **Retry Pattern: exponential backoff**
  - https://cloud.google.com/iot/docs/how-tos/exponential-backoff
- **Many implementation guides and tools, e.g.**
  - https://github.com/resilience4j/resilience4j

# Circuit breaker pattern

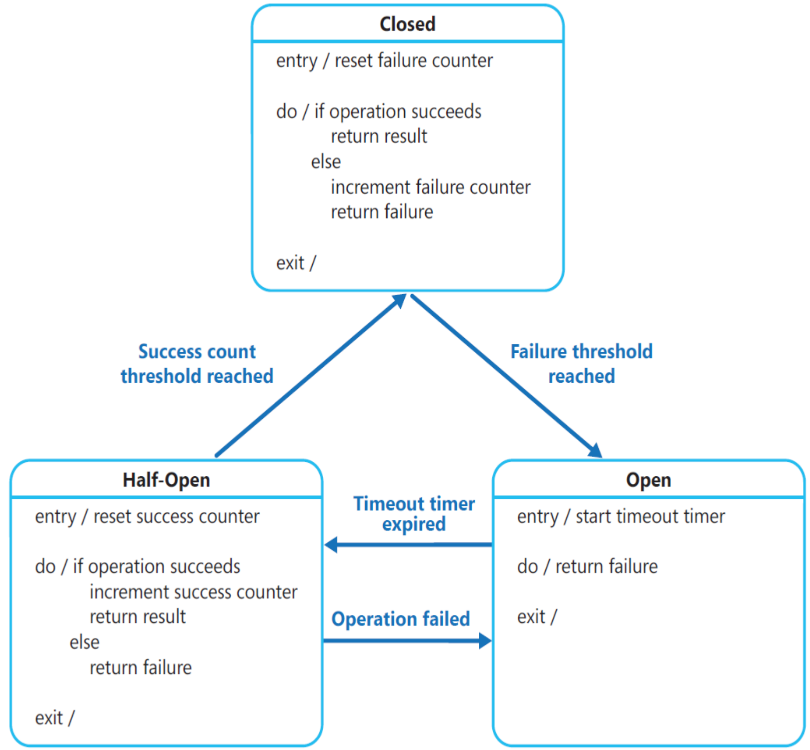

- *What if service operations fail due to unexpected problems or cascade failures (e.g. busy → timeout)*
  - Let the client retry and serve their requests may not be good

**→ Circuit breaker pattern prevents clients to retry an operation that would likely fail anyway and to detect when the operation failure is resolved.**

# Circuit breaker patterm

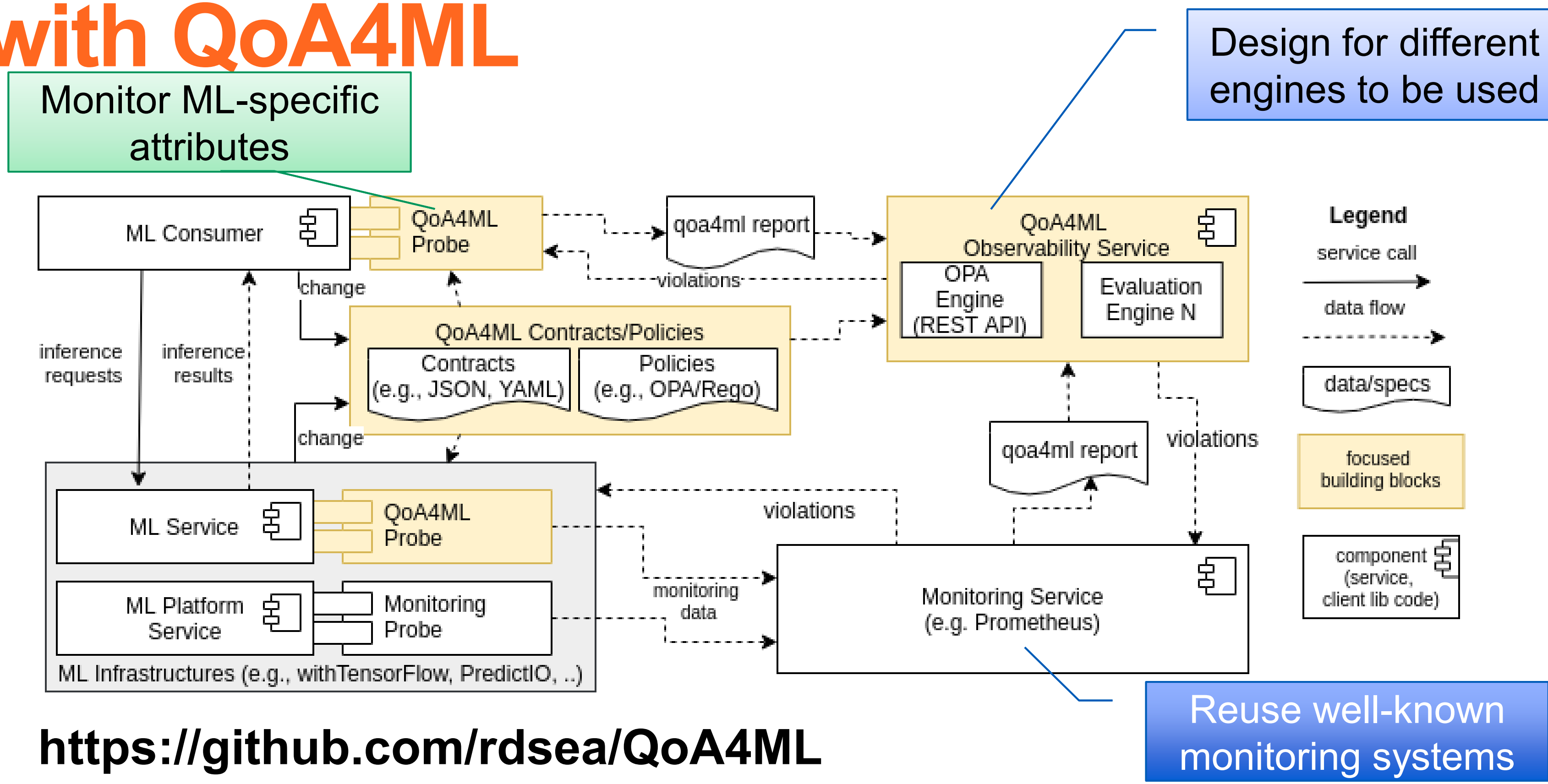



Source: http://martinfowler.com/bliki/CircuitBreaker.html




Source: https://msdn.microsoft.com/en-us/library/dn589784.aspx

# Example: ML contract observability with QoA4ML




**https://github.com/rdsea/QoA4ML**

# Big data/ML for Observability vs Observability for Big data/ML systems

- **Big data  of metrics, logs and traces**
  - Large number of entities to be observed
  - High number of measurement  dimensions
- **ML for observability**
  - Classification, prediction and detection of traffics/interactions anomaly behaviors, hidden relationships, etc.
  - Root-cause analysis
  - ML serving is   in the edge and cloud

# Experiment management

## how do we manage important information for ML services?

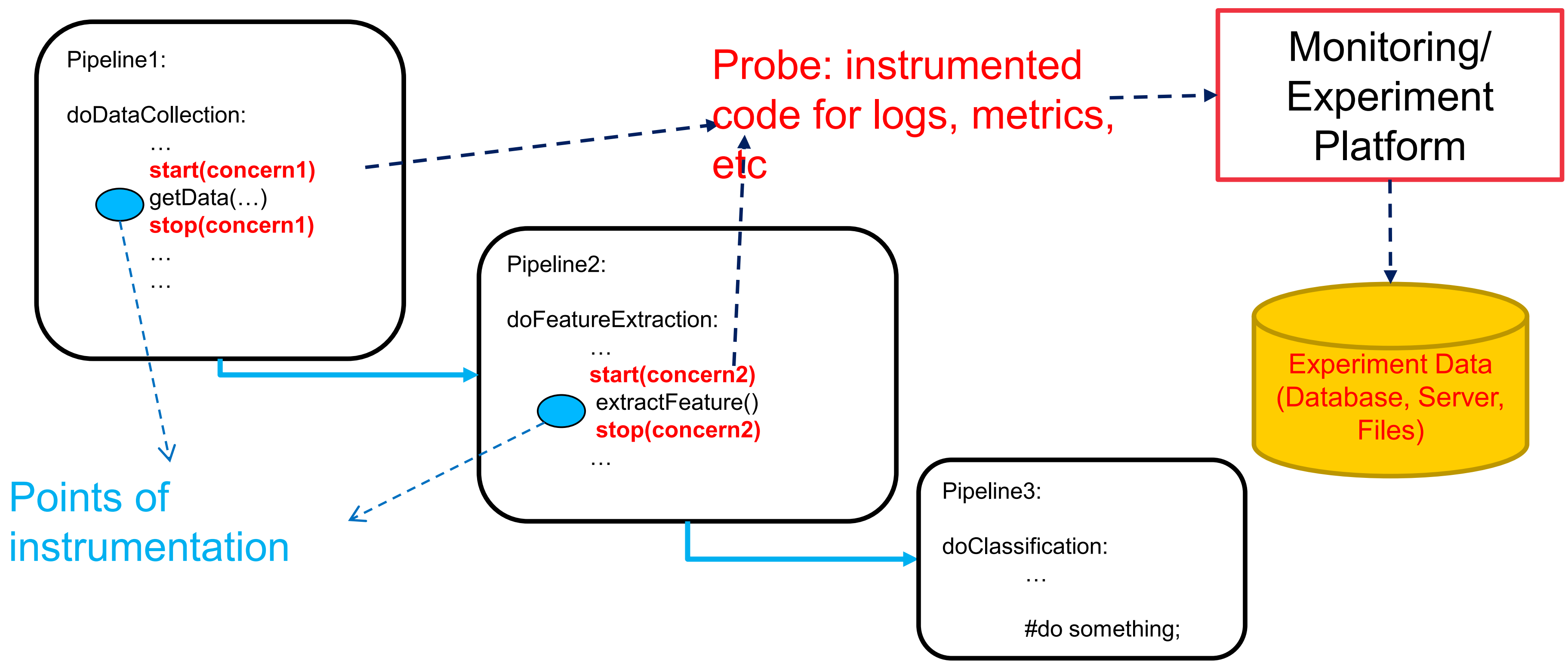
# Problems

- **We need to run many experiments**
  - testability/observability purposes: figure out suitable configurations
  - how does this help to understand and support R3E?
- **Experiment management**
  - known domain and well-known books (e.g., "Design and Analysis of Experiments" by Douglas C. Montgomery)
  - principles: capturing various configurations
  - how does it work in big data and ML?
- **What do we need?**
  - tools/frameworks for tracking experiments

# Notions

- **A single run/trial**
  - inputs, results, required software artefacts
  - computing resources, logs/metrics
- **Experiment**
  - a collection of  runs/trials/executions gathered in a specific context
- **Steps**
  - parameterization: generate different parameters
  - deployment: prepare suitable environments
  - execution:  run and collect  metrics
  - analysis and sharing: analyze experiment data

# Experiment tracking




**But remember it is very large system! Which tools can we use?**

# Examples

- **Tensorflow Board (https://www.tensorflow.org/tensorboard)**
- **Experiment in Azure ML SDK**
  - https://docs.microsoft.com/en-us/python/api/overview/azure/ml/?view=azure-ml-py#experiment
- **MLFlows https://mlflow.org/**
- **Kubeflows**
  - https://www.kubeflow.org/docs/pipelines/overview/concepts/
- **DVC: https://dvc.org/**
- **Verta: https://www.verta.ai/**

# Examples: MLFlow APIs

- **Experiment**

```
mflow.start_run()/end_run()
```

- **Logs/metrics collection**

```
mflow.set_tag()
mflow.log_*()
```

- **Tracking data management**
  - Local files, Databases, HTTP server, Databrick logs

**(follow our hands-on tutorial)**

# Experiment management: more than just ML models

- **Remember there are many components in a system**
- **Experiment data about other components is also crucial**
  - have a full visibility and understanding of the system
  - support explainability and end-to-end optimization
- **ML model experiment must be combined with other types of experimental data**
  - experiment management for end-to-end systems

# Study log 2

**Describe one big data/ML pipeline that you are familiar with and explain your thoughts on how would you support the aspects of "benchmarking", "monitoring", "observability", "experimenting" or "design pattern" for testing/implementing R3E aspects**

- Is enough to focus on 1 pipeline and 1 aspect
- Be concrete, e.g., with metrics and possible tools
- Analyze if things can be done easily or where are the challenges that might be interesting for further investigation
- Optionally link to issues raised/addressed in a reading paper

# Thanks!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